SPLxUTSPAN 2026 Data Challenge

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February 2026

1 Methodology Overview

The objective of this study is to predict basketball free-throw landing outcomes—shot angle, depth, and left/right displacement—using markerless motion-capture data. Each trial consists of three-dimensional trajectories for 71 anatomical keypoints captured across a fixed-length sequence of 240 frames. Rather than relying solely on end-of-motion positions, our methodology models the coordinated biomechanical patterns that emerge throughout the shooting motion, with particular emphasis on late-phase kinematics near ball release. The overall pipeline combines biomechanically motivated feature engineering with a regularized ensemble learning approach designed to balance predictive accuracy and generalization on a relatively small dataset.

2 Data Representation and Preprocessing

All time-series inputs were first parsed into numerical arrays and standardized to ensure consistent length and dimensionality. Because each trial contains exactly 240 frames, we leveraged this temporal alignment to extract phase-specific features without requiring sequence resampling or padding. Missing coordinate values were interpolated linearly to preserve motion continuity while avoiding abrupt discontinuities that could bias derivative-based features. The training split contains an unequal number of trials per participant (pid 1: 70 samples, pid 2: 66 samples, pid 3: 68 samples, pid 4: 67 samples, and pid 5: 74 samples), which introduces variability in participant-level learning and further motivates the use of globally trained models.

A key component of preprocessing is the estimation of a release frame. Instead of using a fixed index, release timing was approximated by detecting the peak magnitude of wrist velocity, computed from frame-to-frame positional differences in three-dimensional space. This approach is grounded in biomechanics literature, where distal segment velocity often peaks near ball release. The identified release index serves as a reference point for constructing localized temporal features that emphasize the most informative portion of the motion.

3 Biomechanics-Informed Feature Engineering

Given the relatively small number of trials, the modeling strategy relies heavily on transforming raw coordinates into interpretable biomechanical descriptors. Feature engineering was organized into several complementary categories.

Statistical Motion Descriptors. For each coordinate trajectory, we computed descriptive statistics including mean, standard deviation, extrema, temporal slope, mean absolute frame-to-frame change, and missing-value fraction. These features provide stable summaries of motion patterns while reducing sensitivity to noise.

Phase-Based Temporal Features. Because all sequences contain 240 frames, the motion was divided into three biomechanical phases representing preparation, loading, and release. Velocity magnitude statistics for key joints (wrist, elbow, shoulder, and mid-hip) were computed separately within each phase. This representation captures how energy builds and transfers through the kinetic chain, which is closely linked to shot trajectory.

Release-Centered Kinematic Features. A temporal window centered on the estimated release frame was extracted for shooting-side joints. Within this window, we calculated fingertip snap speed, finger spread distances, and finger curl angles to represent fine motor control during release. These localized descriptors were designed to capture subtle variations in hand mechanics that influence ball angle and rotation.

Geometric Skeleton Features. Distances between anatomically meaningful joint pairs (e.g., shoulder–elbow, elbow–wrist, hip–knee) were computed to encode limb extension and body alignment. Additionally, joint angles derived from three-point geometry were used to capture elbow, shoulder, and knee articulation patterns. Angular representations provide rotational information that is often more stable than raw positional coordinates.

Key-Frame Pose Snapshots. To exploit the fixed-length sequences, pose snapshots were extracted at late frames corresponding to approximately 75%, 85%, 92%, and 98% of the motion. For each snapshot, we computed elbow angle, wrist velocity direction, and limb orientation vectors. These features serve as compact representations of shooting posture at critical stages leading up to release.

Shooting-Side Identification. The shooting arm was automatically identified by comparing peak wrist velocities between the left and right sides. A binary indicator representing shooting handedness was included as a feature to help the model interpret asymmetric motion patterns.

4 Modeling Approach

The predictive model consists of separate ExtraTrees regression ensembles trained for each target variable. Tree-based ensembles were chosen because they handle nonlinear feature interactions, require minimal preprocessing, and perform well under high-dimensional tabular inputs. Extensive experimentation demonstrated that moderate tree depth combined with feature subsampling provided the best balance between expressiveness and regularization. The final configuration uses a limited maximum depth and partial feature sampling to mitigate overfitting.

Although participant-specific models were explored, global models trained across all players yielded more stable leaderboard performance, suggesting that common biomechanical patterns dominate individual variability under the competition metric.

5 Evaluation Alignment and Scaling

Predictions were generated in raw physical units and subsequently scaled using the provided MinMax bounds prior to submission. Output clipping ensured that predictions remained within physically plausible ranges. Because the evaluation metric computes mean squared error on scaled targets, careful alignment between modeling outputs and scaling procedures was essential.

6 Experimental Strategy

Model development followed an iterative process emphasizing interpretability and stability. Initial experiments explored alternative ensemble methods; however, ExtraTrees consistently outperformed gradient boosting approaches, likely due to the high correlation among engineered features and limited sample size. Subsequent improvements were achieved by refining phase-based features and incorporating late-frame kinematic snapshots, which better capture the mechanics governing shot angle. These observations highlight that performance gains were driven more by biomechanical feature selection than by increasing model complexity, reinforcing the importance of domain-informed representation learning under limited data regimes.

7 Data Size Constraints and Feature Engineering Trade-offs

A central limitation of this study is the imbalance between dataset size and feature dimensionality. Although the motion-capture recordings provide rich biomechanical detail, the training split contains only a few hundred trials while the engineered feature space exceeds several thousand dimensions. Under such conditions, expanding the feature set does not necessarily improve predictive performance. In practice, additional handcrafted features occasionally led to worse leaderboard scores, suggesting that the model began fitting noise rather than meaningful biomechanical structure.

This observation reflects the classical bias–variance trade-off: as feature complexity increases, model variance grows substantially when sample size is limited. Tree-based ensemble methods are particularly sensitive to high-dimensional correlated inputs, where small fluctuations in the data may appear as spurious predictive patterns. Consequently, aggressive feature expansion was intentionally avoided in the final design.

Instead, the methodology prioritizes biomechanically grounded features concentrated around the release phase, where physical relevance is strongest. By constraining feature engineering to interpretable kinematic descriptors rather than exhaustive transformations of the entire trajectory, the model achieves a more stable balance between expressiveness and generalization.

8 Limitations and Future Work

While the current approach leverages fixed-length sequences to incorporate temporal structure, it still summarizes motion through handcrafted features rather than modeling full trajectories directly. Future work could investigate phase-normalized representations, lightweight temporal neural networks, or physics-informed trajectory modeling. Incorporating ball-tracking data or explicit force-transfer estimates may further improve predictive performance, particularly for angle estimation.

9 Conclusion

This methodology integrates biomechanics-driven feature engineering with a regularized ensemble learning framework to predict free-throw landing outcomes from full-body motion capture data. By exploiting fixed-length sequences, release-centered kinematics, and phase-specific motion patterns, the model captures both global coordination and fine motor control. The resulting system emphasizes interpretability, robustness, and strong quantitative performance within the constraints of a small but information-rich dataset.